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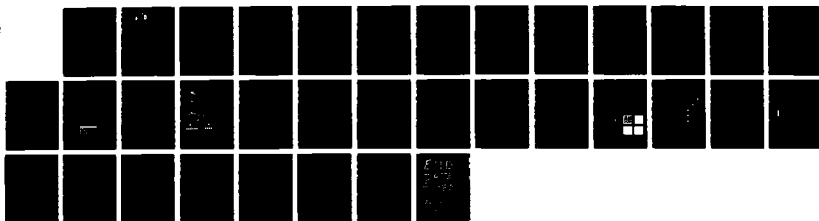
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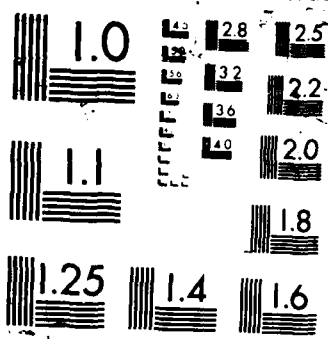
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19. Abstract (continued)

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Rapid Feature Extraction Via
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FINAL REPORT

for Grant Period 1 Oct 1985 to 1 Dec 1987

for: Air Force Office of Scientific Research
Bolling AFB
Washington, DC 20332

1 Summary

In this work, the investigators explored the area of neural-net associative memories and their optical implementations. We addressed the problem of organizing an associative memory to reflect known structure in the pattern. Because the structure is encoded as a model in the memory, the memory differs considerably from simple pattern matchers (such as the Hopfield content-addressable memory) where an iconic version of the pattern itself is stored. Early work concentrated on the idea of encoding a compositional hierarchy within the memory. A simulator was built to explore the use of this memory in a domain of simple shapes. Though this worked well, the theory was inadequate to explain and predict the behavior of the memory. An optimization approach was adopted in which the goal of the computation could be succinctly stated in a mathematical objective function. In this work, the ideas of compositional as well as inheritance hierarchies were encoded directly into the objective function. A simulator was completed that demonstrated these ideas. Optical implementation of this type of memory was concerned with the problem of implementing ever more general interconnect patterns. The investigators began with the construction of a system that computed Radon Transforms of the input object. This award-winning work demonstrated the necessary first step of an optical connection scheme to transform objects to parameter spaces, but it was limited in scope. A more complex system was built that demonstrated discrete space-invariant connection patterns. This worked satisfactorily. The current work involves designs for holographic space-variant connection patterns.

2 Introduction

The following is a summary of progress accomplished over the two-year grant period. A number of papers, Tech reports, etc. are referenced at the end of this Final report.

The overall theme of the project was the investigation of issues in the organization of visual memory. The project was pursued at the theoretical level as well as at the level of hardware organization, where issues in the optoelectronic implementation of these memories were pursued.

This project grew out of earlier work in optical pattern recognition. In this earlier work [23], it was attempted to compute (at very high speeds) features of objects for the purposes of recognition. An important feature that we considered was the Hough Transform, basically the mapping of the input image into a parameter space. It was noted that the design of a certain class of associative memories was based on a generalization of the Hough Transform [18]. This generalization led to the present work in neuromorphic associative memories.

Below we list a summary of accomplishments completed during the grant period. This is followed by a more detailed discussion.

3 Summary of Completed Research

Below is a succinct summary of accomplishments of the grant period. Each item is followed by a reference to an appropriate paper or technical report that gives a more detailed account.

- The development and implementation of a system for shape recognition [6], [7] was completed. This program matches *structural* (graph) descriptions of shape to a database of structural models that are arranged hierarchically to permit indexing. In addition, work on a shape-parsing program — a program that forms structural representations from input images—was completed [9].
- We developed an optimization-based neural net to implement the structural pattern recognition tasks mentioned above [49]. [50]. We show results of this in the body of the Final Report.
- In our effort to explore distributed representations, we analyzed Winner-Take-All (WTA) networks and devised a new WTA architecture based on linear threshold units [14].
- We analyzed the “unfolded” version of the Hopfield associative memory and showed that it evolved in a manner somewhat different than that of the original model [16]. We performed a statistical analysis of this version for randomly coded memories and showed that this version exhibited improved performance [16].
- We completed work on a neural net that implements a three-level compositional hierarchy in the domain of simple pattern recognition [19] [21]. This work was a necessary precursor to our current efforts.
- We wrote a fairly elaborate neural-net simulator for use as a development tool [22]. The simulator allows the user to conveniently design and monitor the network through a graphics interface. It is available to other members of the research community.
- We evaluated the technological alternatives available to the implementation of optical neural networks.
- We built a simple optical neurocomputer for the solution of the correspondence problem in stereo vision. Our interest was not in the stereo problem, but in the particular space-invariant connection pattern associated with this problem. Several alternative architectures were constructed and evaluated including a system that used time multiplexed connection patterns and a system that implemented a two-channel bias subtraction technique. The later architecture is amenable to all-optical neural networks. The results of this work were presented at the upcoming IEEE conference on neural networks[48] and are discussed in the body of this Final Report.

4 Discussion

The work is best described within three categories. The first concentrates on issues in the design of a model-based associative memory described above. The second focusses on some of the detailed issues in the design of such memories; the third area involves issues in optical hardware implementation of associative memory.

4.1 Visual Memory

In this section we consider the problem of deriving an associative memory for the storage and matching of structural representations of visual patterns. Appropriate questions here were:

- What is a suitable structural description of a visual pattern?
- How are the descriptions themselves organized for efficient indexing?
- How is all this represented in a neural network?
- What is a suitable objective function for optimization?

We consider each item and point out progress made.

4.1.1 Representation and organization of visual memory

In order to implement a neuromorphic associative memory that works on structural representations of visual patterns, it was necessary to first invent a suitable representation. Substantial progress has been made in this area, and the results are summarized in two papers [6] [7].

The representation is described in a domain of simple stick figure shapes and follows the general requirements of a shape representation as given by Marr and Nishihara [8]. As seen in Fig.1, these stick figures may be assumed to have been derived from a preprocessor that is able to parse the shape into elongated regions described by generalized cylinders[2]. For the present case, we assume that the shape is simple enough that a linear axis is sufficient to describe the elongated region, thus reducing the shape to a stick figure. While it is clear that a linear stick-figure is far too simple a representation for a sophisticated vision system, we emphasize again that the problem lies not in the area of design of advanced vision systems, but in its neural implementation. In this case, the challenge is considerable.

In fact, we made progress in much more elaborate shape parsing systems as reported in [9], but the description produced by this system was too complex to use in the neural net implementation. The work in [9] was able to take a shape in the form of a 2-D closed contour and segment it into elongated regions based upon heuristics. Each region had a set of symbolic descriptors associated with its contour and its interior. Included also were symbolic descriptors of the joins between regions.

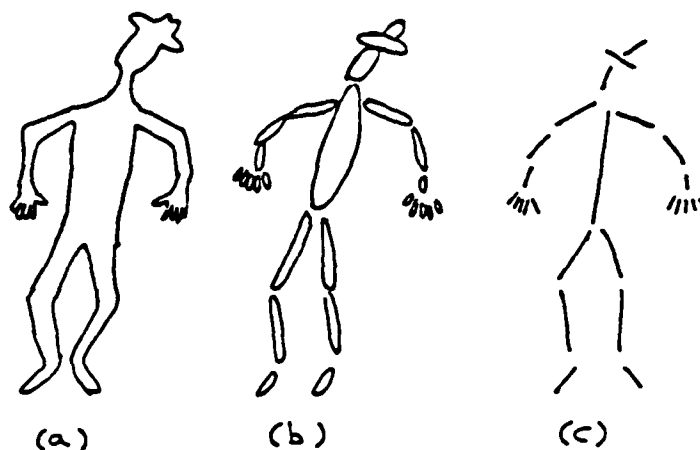


Fig. 1: Axis Based Description.

A silhouette represented as elongations and axes.

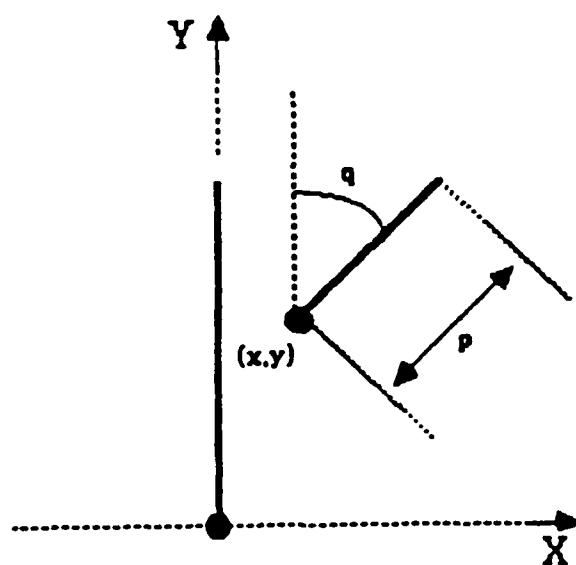


Fig. 2: Adjunct relations.

Geometrical parameter of one stick are relative to a coordinate system centered on another.

The important aspects of this shape representation were that it was able to represent objects independent of scale, translation, rotation; and was able to organize shapes into inheritance and compositional hierarchies to allow efficient indexing. Thus a model could be accessed by verification of its parts, and by focusing attention on those models which were shape descendants of models higher up in the discrimination tree. Parent-child relationships could be defined geometrically with the aid of shape parameters [6].

4.1.2 Neural Implementation

The basic idea here was to have the nodes of the neural network represent matching hypotheses between memory and input, and have the connection weights encode the models and input object. This work is described in [50] and [49] and is briefly reviewed here.

A node in the network $M_{X,s}$, is labelled by X , which indexes "objects" and "parts" in the memory (the distinction between these blurs) and by s , which indexes parts (sticks) of the input scene. The value of the node reflects the confidence that object X is matched with stick s and is essentially the definition of a node in a graph-matching network proposed by Mjolsness[11]. The value of M may be taken as a real number between 0 and 1.

The IS-A inheritance hierarchy that organizes objects in the database is captured in a sparse binary matrix $ISA_{X,Y}$ defined as unity if object Y is a child of object X in the IS-A tree hierarchy and zero otherwise. For example, $ISA_{plane,jet} = 1$ while $ISA_{mammal,jet} = 0$ in the IS-A tree. The IN-A hierarchy in the model database is captured by a sparse binary matrix $INA_{X,Y}$ that is unity if part Y is a child of part X in the L-level decomposition tree of the model. Similarly, the sparse binary matrix $ina_{s,t}$ captures IN-A relationships of the input data. The $ina_{s,t}$ matrix is unity if stick t is a child of stick s in the L-level decomposition of the input scene, and is otherwise zero. These three matrices thus constitute the necessary data items that capture the organization of memory and input object. We defer consideration of representing adjunct relations and instances to material below.

Given this organization of the data structures in terms of sparse matrices, the problem is to formulate an objective function that assumes local minima when an input object matches a model. The objective function is composed of three terms, conveniently referred to as the "triangle" rule, the "choose" rule and the "rectangle" rule[11]. Consider the situation shown in Fig 7. The triangle represents a situation where $ISA_{X,Y} = 1$, that is, object Y is a specialization of object X . If stick s is matched as the mainpart of object X , then the objective function should be lowered in the matching situation where stick s is also the mainpart of the more specialized object Y . The proper term in the objective function that captures this rule is the quadratic

$$E_1 = -A \sum_X \sum_Y \sum_s ISA_{X,Y} M_{X,s} M_{Y,s} \quad (1)$$

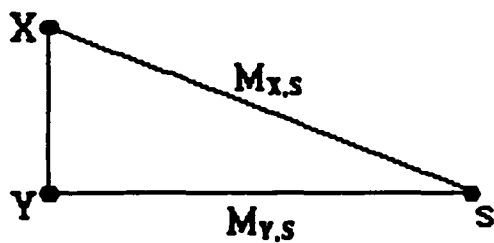


Fig. 7: Triangle Rule.
Schematic form for
the triangle rule. !

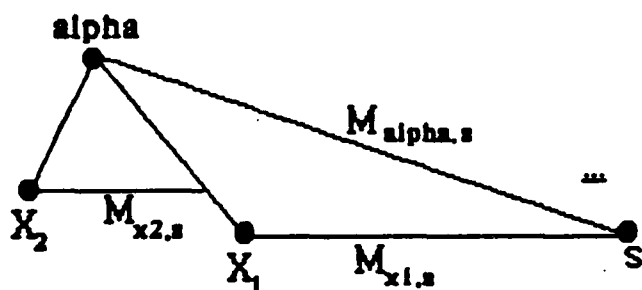


Fig. 8: Choose Rule.
Schematic form for
the choose rule.

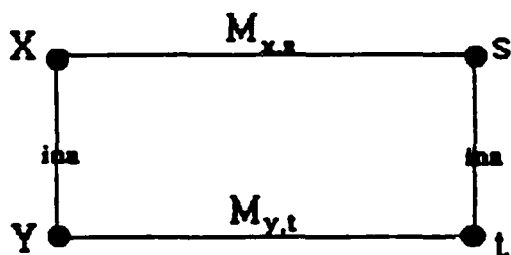
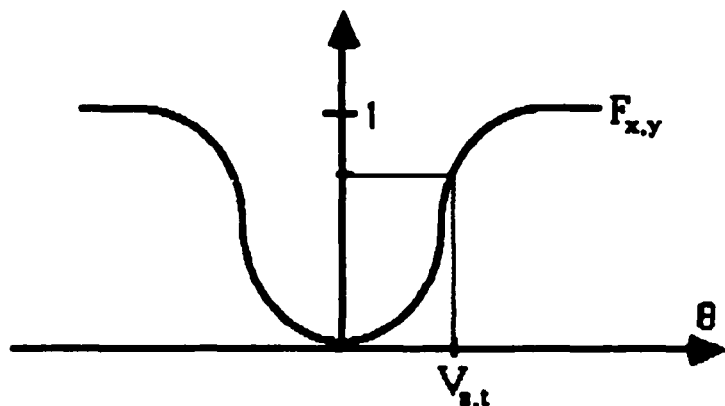


Fig. 9: Rectangle Rule.
Schematic form for
the rectangle rule.



**Fig. 10: Conditional
Parameter Relationship.**
A condition on the allowed
parameters on the angle
between two sticks shown
as a functional relationship.

where A is a constant.

The "choose" rule implements the notion that, given several competing children nodes of a parent node in the IS-A hierarchy that are all match candidates for a common stick s , only one child should be activated. For example, a plane is a jet or a propeller plane, but not both. It is possible to ensure this exclusive-or condition by suitably defining parameter ranges. The choose condition is illustrated in Fig. 8, where object α is the parent in the IS-A hierarchy of objects X_1 and X_2 . One would like the objective function to be a minimum when one of the terms $M_{X_1,s}, M_{X_2,s}, \dots$ is unity and the rest zero. This is achieved by minimizing the term

$$E_2 = +B \sum_{\alpha} \sum_s [\sum_X ISA_{\alpha,X} M_{X,s} - 1]^2 \quad (2)$$

Here, the index X runs over objects X_1, X_2, \dots that are children of parent object indexed by α , and the index s runs over candidate sticks in the input scene. The term B is a constant.

The "rectangle rule" implements the parameter range matching. It says essentially that if items X and Y are related by an *INA* relationship defined by suitable parameter ranges, and if sticks s and t are related by an *ina* relationship associated with instances of parameters p, θ, x, y that fall within the ranges, then the matches $M_{X,s}$ and $M_{Y,t}$ should be increased. For example, two sticks in the object that are consistent with geometrical relationships stored in a wing-engine model should activate an increase in the two match nodes that hypothesize matches between wing and its allied stick and engine and its allied stick. This situation is illustrated in Fig. 9 where X, Y, s , and t are arranged as a rectangle with the matching nodes on the horizontal links and the *INA* and *ina* entries on the vertical links. The appropriate term in the objective function for this situation is:

$$E_3 = -C \sum_X \sum_s \sum_Y \sum_t M_{X,s} M_{Y,t} INA_{X,Y} ina_{s,t} \mathcal{F}_{X,Y}(V_{s,t}) \quad (3)$$

where C is a constant. The sum of the three terms $E_1 + E_2 + E_3$ is the objective function for our system.

The term $\mathcal{F}_{X,Y}$ is a function of the the four adjunct parameters and is indexed by the IS-A link between X and Y . Its argument is $V_{s,t}$, a vector consisting of the values of the adjunct variables existing between s and t . If the values fall well within the ranges allowed by \mathcal{F} , a low value is returned; else it is high. Fig. 10 shows a plausible depiction of \mathcal{F} as a function of θ where the best values of θ are centered about zero. From this it is easy to see that arbitrary relations, not just simple inequalities may be implemented in the adjunct relations. Though \mathcal{F} has been treated as a hardwired data item, we point out that it is possible to modify it with a learning procedure. A relevant discussion for the non-neural case is found in [5].

Figure 11 shows how the triangle and rectangle structures are arranged in order to capture the organization of the memory. In this example, the object "root"

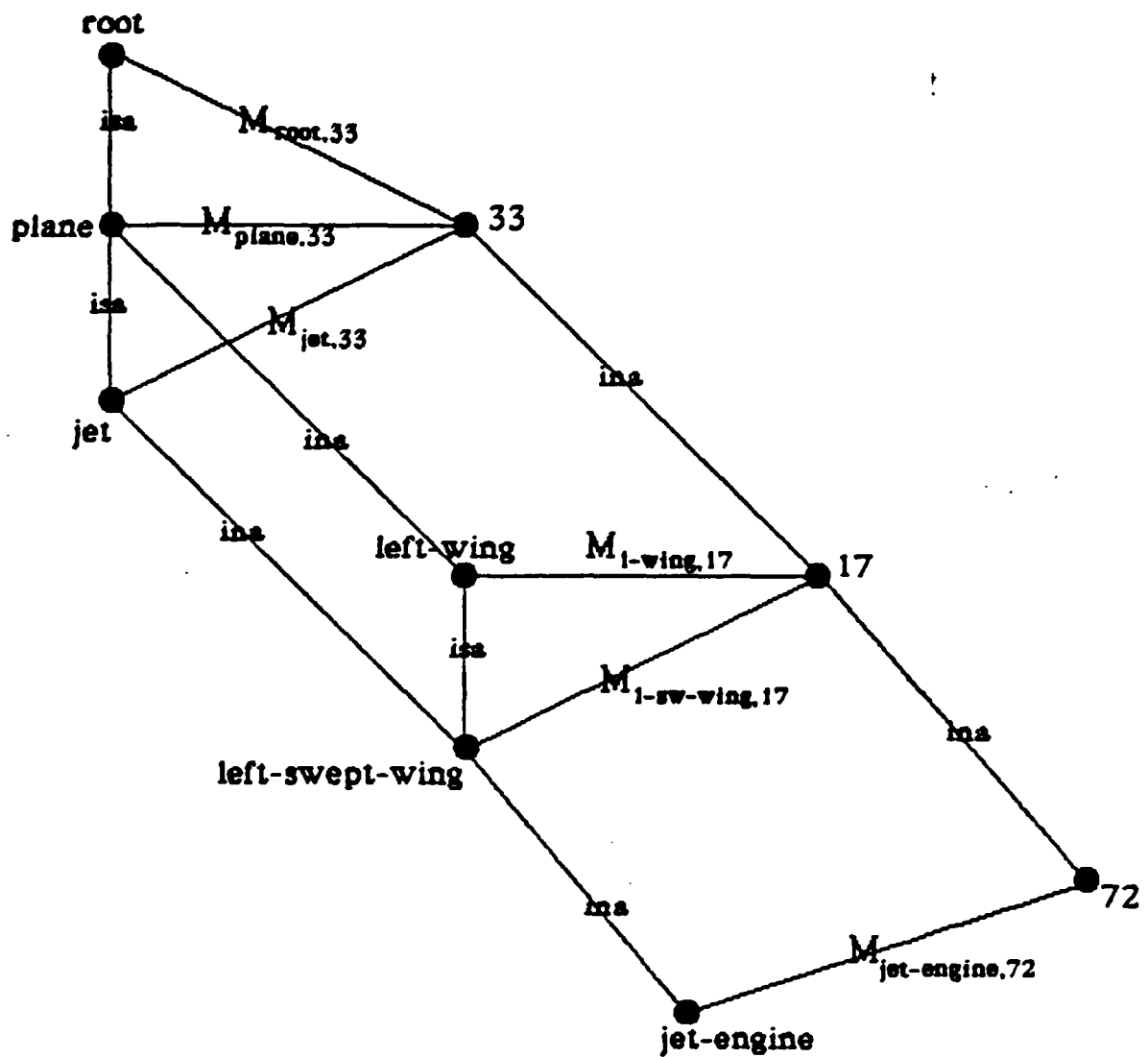


Fig. 11: Network implementation of
inferencing structure.

Cascade of triangles and rectangles
illustrates organization of the network.

is linked via the IS-A hierarchy to an object "plane" via a triangle structure. Of course, other triangles associating "root" with "mammal" or other high-level objects are not shown. Shown is the triangle associated with stick 33 in the input scene. The node $M_{plane,33}$ receives bottom-up support from the rectangle structure associated with "plane", stick33,"left-wing", and stick 17. Only one rectangle is shown; but one for each part would, in fact, be present. Object "plane" is specialized to "jet" via the lower triangle shown. The polygon formed by the four links $ISA_{plane,jet}$, and $ISA_{left-wing,left-swept-wing}$, and $INA_{plane,left-wing}$ and $INA_{jet,left-swept-wing}$ implement the specialization action of the shape indexing system. For plane to specialize to jet, the wing must become a swept wing. Two mechanisms make the wing a swept wing: The parameters become more specialized in that the parameters stored in $V_{33,17}$ associated with stick 17 relative to 33 satisfy the more stringent $\mathcal{F}_{jet,left-swept-wing}$ requirement instead of the lax $\mathcal{F}_{plane,left-wing}$ function. This specialization is thus implemented by the polygon and two rectangles. The specialization may be further enhanced by finding additional parts that define a left-wing as a left-swept-wing. This latter situation is shown by the rectangle that posits a jet-engine as part of a swept-wing. In this manner of cascading, the network is organized.

Given the quadratic (in M) objective function, we may calculate the connection weights between nodes and bias terms on each node in a manner following Hopfield and Tank [20]. One merely equates the generic quadratic energy term of any network[12]

$$E = - \sum_{X,s,Y,t} T_{X,s,Y,t} M_{X,s} M_{Y,t} - \sum_{X,s} I_{X,s} M_{X,s} \quad (4)$$

(here written in the appropriate double indices) with the energy terms of the present network and solves for the connection weights $T_{X,s,Y,t}$ and bias terms $I_{X,s}$. The answer is

$$T_{X,s,Y,t} = -A\delta_{s,t} ISA_{X,Y} - B\delta_{s,t} \sum_{\alpha} ISA_{\alpha,X} ISA_{\alpha,Y} - C\delta_{s,t} INA_{X,Y} \mathcal{F}_{X,Y}(V_{s,t}) \quad (5)$$

and

$$I_{X,s} = -2B \sum_{\alpha} ISA_{\alpha,X} \quad (6)$$

These two terms determine the structure of the network. The dynamics follow [20] the prescription:

$$du_{X,s}/dt = -(u_{X,s})/\tau + \sum_{X,s,Y,t} T_{X,s,Y,t} M_{Y,t} + I_{X,s} \quad (7)$$

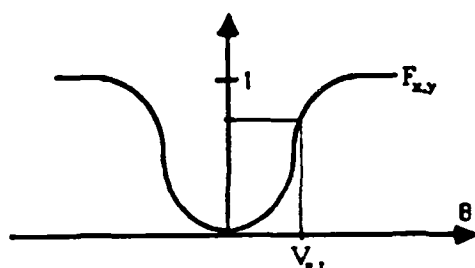
where τ is a constant and $M = g(u)$ is a monotonic sigmoidal mapping. The objective function is minimized as the network updates by the above differential equation.

ACCOMPLISHMENTS

VISUAL MEMORY: DESIGNED AND IMPLEMENTED WORKING VISUAL MEMORY FOR DOMAIN OF STICK-LIKE OBJECTS.

INPUT: SPARSE BINARY MATRIX ina_{st} STORES STRUCTURAL REPRESENTATION OF INPUT IMAGE. MATRIX IS UNITY IF PARTS s AND t SATISFY PART-OF DEFINITION. PARAMETER VECTOR P_{st} STORES GEOMETRICAL RELATIONSHIPS BETWEEN PARTS.

MODEL: SPARSE BINARY MATRIX ina_{xy} STRUCTURAL REPRESENTATION OF MODEL. MATRIX IS UNITY IF MODEL PARTS x, y ARE PARTS OF SAME OBJECT. NOTION OF SIMILARITY CONTAINED IN FUNCTIONAL FORM F_{xy} . THEN $F_{xy}(P_{st})$ IS A NUMERICAL MEASURE OF HOW WELL GEOMETRICAL RELATIONSHIPS OF PARTS s AND t FIT MODEL REQUIREMENTS BETWEEN PARTS x and y .



Conditional
Parameter Relationship.
A condition on the allowed
parameters on the angle
between two sticks shown
as a functional relationship.

MATCHING: PROBLEM IS REPRESENTED BY MATCHING NEURONS M_{xs} THAT EQUAL UNITY IF NODE x IN MODEL DATABASE MATCHES PART s IN DATA. NETWORK SETTLES TOWARDS STABLE STATE OF MATCH MATRIX AS SOLUTION TO PROBLEM.

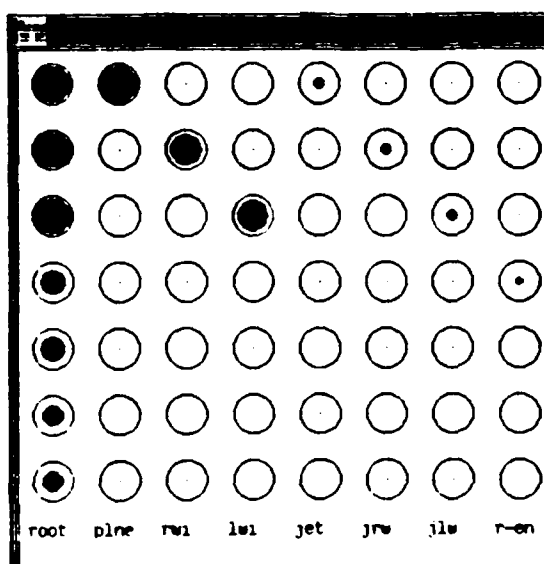


FIG 11a

The system described was simulated on a VaxStation II workstation using extensive visualization provided by graphical representations of the match network. Fig. 11a shows the system displayed as a match matrix. Each circle is a match neuron whose value is coded as the diameter of the blackened interior region. Its column indicates to which model it belongs while its row indicates to which stick it is being matched. As shown the system is in an intermediate state: it has matched the parts of an airplane and is successfully on its way to matching a jet. The jet is a specialization of plane related to it through an ISA hierarchy.

4.2 Distributed Representation

One of the hallmarks of neural network memories is that the items are distributed over many nodes [1]. Such distributed representation is necessary for efficiency in that many memories may share the same nodes; and is necessary for error tolerance in that if a single node fails, only small fractions of each memory are lost. For example, in the visual memory discussed in the previous section, each node posits a single hypothesis (item X matches stick s); if this node is in error, so is the hypothesis since the information is not distributed over many nodes. In this section we discuss problems in distributed representation that were explored in our previous research. We intend to continue this line of work in hopes of deriving better architectures for networks for model-based recognition.

4.2.1 Background

A generic structure within which to discuss the coding (distributed representation) problem is offered in [13] and is illustrated in Fig. 12a. One may think of an associative memory as a three-layer system consisting of an input layer, a processing layer, and an output layer. If the memories presented to the input layer have known structure, for example, they are sparse, then they may be efficiently encoded in an internal representation in the middle layer. The weights on the links between the input and processing layers encode the memories. In this layer, competition between memories occurs until a stable state is reached. The weights on the links between the processing and output layers perform the decoding operation. The emphasis here is not necessarily on learning algorithms that use error propagation techniques to learn codes, but on codes, derived by any means, that lead to efficient and robust representations for the problem at hand.

4.2.2 Alternatives to Outer-Product Memories

Our early work led us to investigate properties of the Hopfield associative content-addressable memory (ACAM) [3]. In the Hopfield ACAM, memories are encoded via an outer-product scheme. It can be shown that the Hopfield ACAM can be

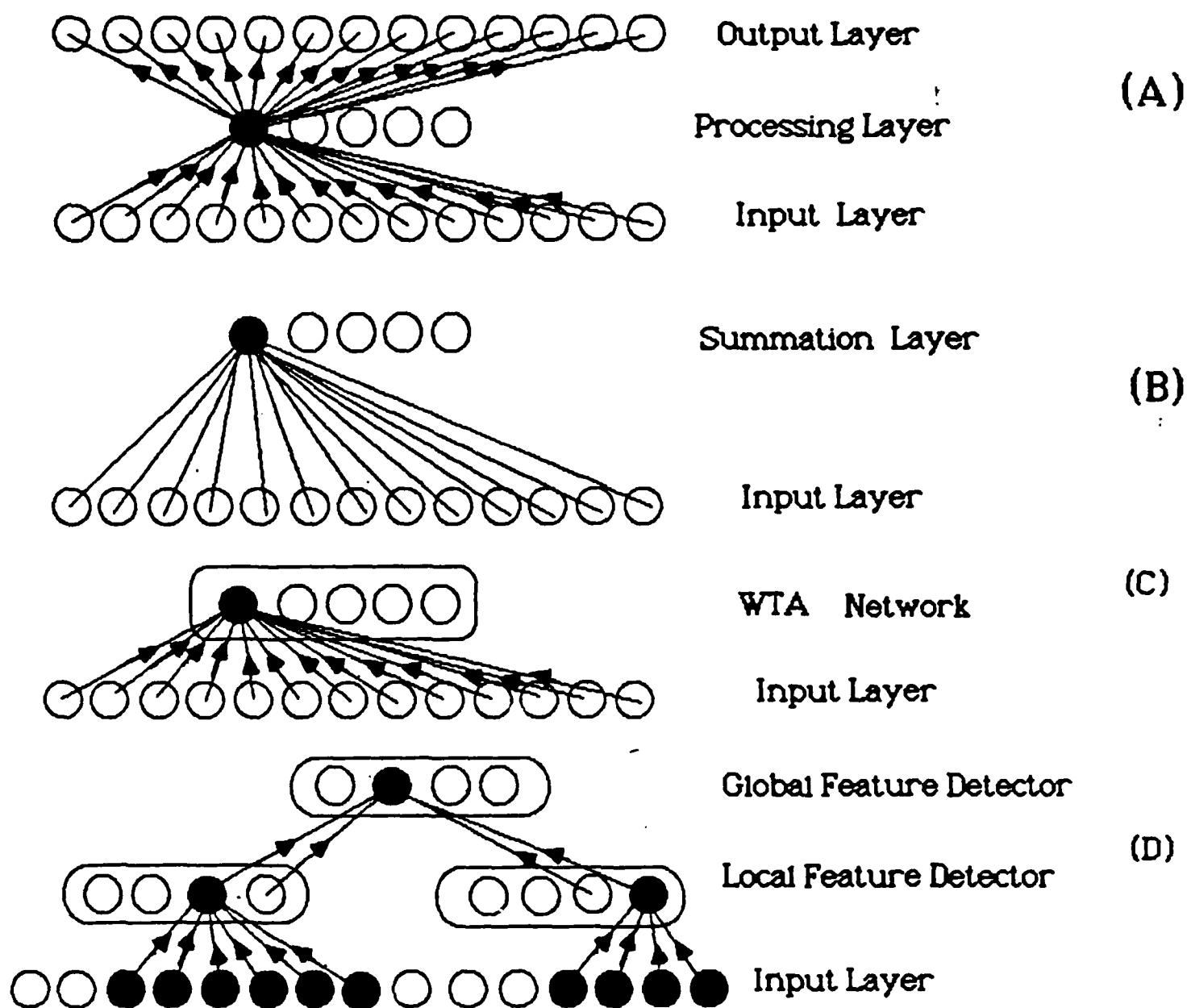


Fig. 12: Networks.

(a) Generic form of internal representation.

(b) Unfolded Hopfield net

(c) Winner-Take-All form

(d) Compositional hierarchy as a partial sum network

cast in the form of Fig. 12b if the proper identifications are made. These identifications associate one processing node with each of the stored memories in the network, and assign the weight between node i of the input layer and node s of the processing layer to be merely the value of bit i of memory s . The decoding links each have weights identical to the encoding links and may be eliminated if the encoding links are considered to be bidirectional. The processing nodes are purely summation units with no thresholding, and there is no internal computation in the processing layer. Rather, the net evolves by iterating back and forth between the two layers until stability is reached. This decomposition or "unfolding" of the Hopfield net is described in quantitative detail in our report [14].

This unfolded representation of the Hopfield net is interesting for several reasons. The representation in the upper layer is unary; each node is a "grandmother" cell associated with one and only one memory, while each node in the input layer is associated with all memories. The weighted links between layers thus translate between two extremes of representation. One line of investigation undertaken explored some of the tradeoffs in going from a totally distributed to a totally unary representation.

The results of this investigation, reported in [14] are briefly summarized. The unfolded net of Fig. 12b is equivalent to the standard 2nd-order correlation Hopfield net that has a storage capacity of roughly N , the number of input nodes. At the other extreme, competition may be removed to the processing layer where a mutual-inhibitory "winner-take-all" (WTA) network chooses the maximum among the analog valued nodes as shown in Fig. 12c. In this case, the storage capacity approaches 2^N , the theoretical maximum and is limited practically by the ability of the WTA network to discriminate closely spaced analog values. In [14], we present an analysis of the relative storage capacities of the two nets given that the WTA version is limited by system noise and the Hopfield net is limited by "crosstalk" between memories. The Hopfield net trades off storage capacity for error tolerance, and the WTA version does the opposite. In [14], we propose a particular architecture for the WTA network. It consists of two intercalated pyramids of linear threshold units.

The Hopfield net may be viewed as a 2nd-order correlation network, and the WTA an N th order one. In between these extremes, a p th-order outer-product memory may be implemented merely by raising processing node values to the power $p - 1$ before projection down to the input layer [15]. As p gets higher, the exponentiation in the processing layer acts more like a max finder in that the ratio of the largest exponentiated value to all others approaches infinity. As p approaches N , the memory behaves identically to the WTA version of Fig. 12c.

Viewed as a dynamical system that minimizes an energy function, we showed that the unfolded version of the Hopfield net in Fig. 12b has a curious property: nodes are updated such that the energy reduction at each step satisfies

$$\Delta E < -C_i \quad (8)$$

where C is a constant associated with each node. For outer-product memories, C equals the number of stored memories; for general networks, it equals the i th diagonal term T_{ii} of the connection matrix. That is, the system looks for sufficiently steep excursions down the energy surface before it changes. This point is discussed in [16] [51]. For randomly coded memories [3], this "greedy" behavior results in improved performance relative to the Hopfield model. An interesting benefit is that optical architectures for outer-product memories naturally follow this unfolded architecture [16] so the improved performance benefits the implementation.

4.2.3 Compositional hierarchy

We described earlier the theme of presenting structured visual patterns as a graph to be matched against similarly structured models stored in a memory. Our earlier interests centered on a somewhat more direct approach of representing structured patterns as a compositional hierarchy of features. This idea of a hierarchy of feature detectors is pervasive throughout the connectionist literature. The basic idea is simple; for example [17], an idealized form of a "chair" is composed of a spatial arrangement of rectanguloids, these are in turn composed of planar rectangular regions which are composed of joined lines and so on. In a connectionist memory, the initial layer is composed of *local* feature detectors, i.e. local upconnects to nodes that posit a low-level feature. These feature nodes serve as input to a higher level whose nodes posit rectangular planar regions; the scheme continues until a complete object is represented by a "grandmother cell" at the apex of the hierarchy. A given node is indexed by its level in the hierarchy and parameters such as location and orientation of the feature.

We built a three-layer compositional hierarchy to recognize arbitrary 2-D shapes structured at three levels of composition: corners, squares, and arrangements of squares. The connection pattern for such memories is local in that a node at layer l upconnects only to those nodes at $l + 1$ of which it can possibly be a part of, and a node at layer $l + 1$ downconnects only to those nodes that might compose it. This Hough transform connection scheme follows principles advocated in [17] and in the "parameter net" architecture of Ballard[18]. The details of our work are presented in [21] [19] and this appears in the Appendix.

A rather elaborate neural-net simulator was built to run this compositional hierarchy. This simulator described in [22], allows the user to engineer and run the net interactively with a mouse. The state of the net is presented in iconic forms to the user. We continue to use it and variants of it for our current work.

The uplinks in compositional hierarchies are just the IN-A links of our model-based neural net described earlier, and the downlinks are just IS-A links; but the links connect nodes that directly posit features in the input image instead of positing matches between elements of a model and the input. Because the nodes represent the pattern directly (iconically), the compositional hierarchy does not enjoy the advantages of a structural representation outlined earlier.

Our compositional hierarchy was *ad hoc* in that no correctness measure, such as an objective function, was used to design the network. We realized that it is indeed possible to store memories that are the minima of an objective function in a compositional hierarchy if we replace the threshold units at higher layers with summation units as shown in Fig 12d. Here, the links are bidirectional and the net acts as a Hopfield memory. Because the memories are structured, far fewer links are needed than in a structured memory.

While the general idea of a compositional hierarchy has been abandoned in favor of the optimization approach, the idea of coding structured memories with local feature detectors is attractive [13].

4.3 Optical Implementation of Neural Network Models

Our interest in the optical implementation of neural network models is an outgrowth of previous work in the area of optical computing systems for visual pattern recognition. We built an optical system for the rapid delivery of image features[23]; many of the features discussed in that paper have invariance properties that make them attractive for use in pattern recognition. One of the feature spaces discussed, the Hough transform[24], is a technique for recognizing image primitives (in our case straight lines) that can be described by a limited set of parameters; in the case of straight lines the slope and intercept parameters completely specify the line. In the optical system we constructed, the connection pattern was implemented in a time multiplexed manner as a series of positions of a cylindrical lens.

Part of the work to date has been to identify what it is an optical neural network should be able to do and then how to best build one in hardware. It seems painfully clear to us that any difficult problem, such as vision, requires an approach that breaks the problem into subproblems of a manageable size. These subproblems, it is hoped, are such that they can be solved efficiently in a neural network that is itself of a manageable size. The solution to one subproblem will direct the attention of the system to another subproblem, much as in the indexing structure of the shape recognition system discussed in the previous section. We envision a system such as shown in Fig. 13. The problem formatter is a high level controller that takes in input from the world and, together with results from previous subproblems, directs the neural network to solve a particular subproblem. The neural network problem solver is basically a network whose nodes and interconnection weights are loaded and then allowed to run (converge) to a solution. The subproblem memory contains the connection pattern required for each of the subproblems and potentially any of the node values that should be preset for that subproblem. Data nodes or input nodes are set by the formatter. The overall structure of the problem solution can be interpreted as a controlled sequence of optimization subproblems.

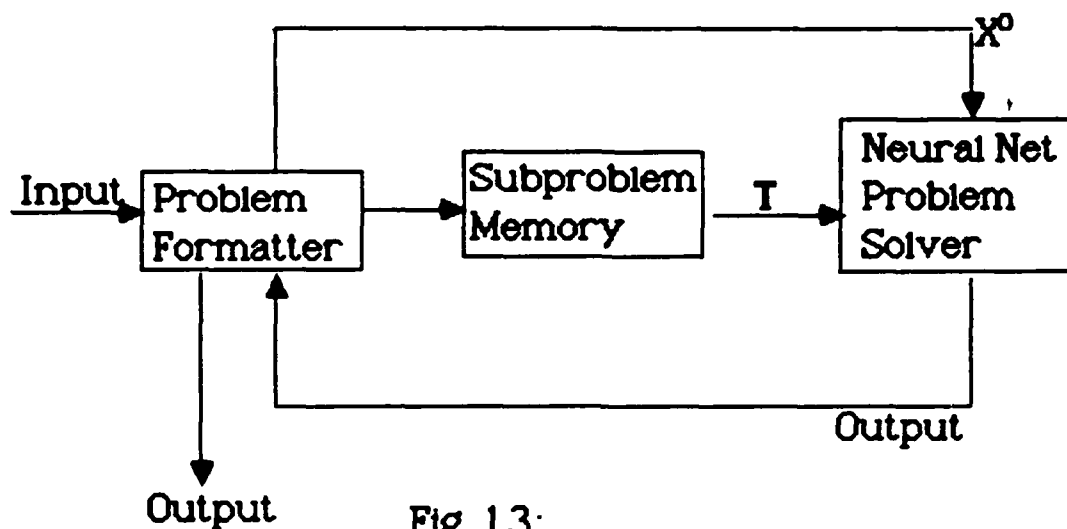


Fig. 13:
Generalized architecture for high level problem solution via subproblem delineation. The matrix T represents the connection matrix and X^0 the initial node values for the neural network.

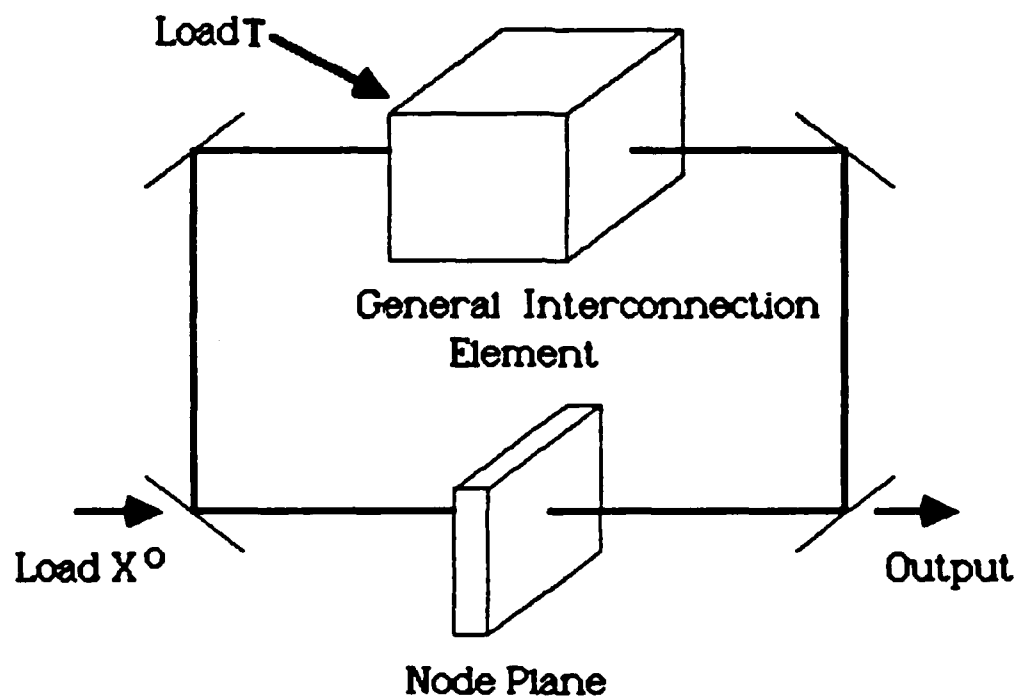


Fig. 14
Generalized architecture of an optical neural network problem solver

We envision the neural network problem solver as an optical computing engine that can be updated or controlled to solve any neural network optimization problem, or associative memory problem, whose size falls within the upper bound of the network. The neural network itself consists of two fundamental structures: nodes and interconnects. The generic structure of the neural network is shown in Fig. 14. The interconnection element is capable of generally interconnecting the node outputs to the node inputs with arbitrary bipolar continuously-valued connection weights; the nodes themselves perform a nonlinear mapping from input to output, where the node values can also be continuously valued. Part of the work to date has been to identify the alternative technologies that might be employed in the implementation of this type of network. Our first year progress report was an elucidation of these alternatives. Basically the technological alternative we have identified are outlined below:

- Nodes
 1. Electronic detection, nonlinearity, and display
 2. Spatial light modulators (e.g. Hughes LCLV)
 3. Nonlinear Fabry-Perot etalons
- Interconnects
 1. Lenslet array and mask
 2. Spatially multiplexed planar hologram
 3. Volume hologram

There are a multitude of possible system configurations that can be conceptualized for implementing the neural network problem solver. Each has its advantages and disadvantages, and each creates a set of problems that needs to be addressed. We have reached some conclusions concerning the technologies that seem to offer the greatest potential for success for the overall system concept described above, but, before discussing the approach, we will first describe a simple neurocomputer that was built which helped us define and delineate the important attributes of an optical neural network.

An extremely simple problem was chosen as a first shot for network implementation. The problem is that of stereopsis, or stereo vision. The general problem is to determine the depth of surfaces in the environment from the two views detected at each eye. The problem is trivial when a single point object exists; a triangulation using the image points and the known vergence point of the eyes yields the correct result. For more complicated scenes, such as random dot stereo patterns, the problem becomes much more complex because it is difficult to know which points correspond in the two views. The general problem is reduced to solving this so-called "correspondence" problem. Once the proper pairs are identified, the depth can be easily determined using triangulation. Marr and Poggio[47] described an algorithm for solving the correspondence problem which, from a computational point of view, can be solved by a neural network. In the network, nodes represent hypotheses about the existence of a surface patch at

a particular depth and the connections encode the constraints about the world (surfaces are opaque and tend to be continuous).

We chose this particular problem because the connection pattern between nodes was simple and space invariant. The details of the optical implementation of this network were presented at the IEEE Neural Net conference[48]. This problem, though simple, was significant because it did require bipolar connections (both inhibitory and excitatory links exist in the network). As seen in Fig. 13, a two-channel incoherent optical system was employed; one channel implemented the positive connection pattern and the other channel implemented the negative connection pattern. This Figure also shows the actual resulting output of the optical neural net and its close comparison to the digitally computed result. The necessary difference operation was obtained in two different ways. In one approach the two images were electronically detected, stored, subtracted, mapped through a nonlinearity, and redisplayed. In the other approach, two displays were used; the nodes in the negative channel were represented as a subtraction from a bias. The action of the node plane was simply to sum the positive channel light and the negative channel light and to apply a nonlinear threshold. This result was mapped through a linear lookup table to the positive display and through an inverted lookup table to the negative channel display. The reason this approach was investigated is because it can be implemented all optically using the transfer characteristics of standard spatial light modulators or nonlinear Fabry Perot etalons. Using either of these technologies, an all optical neural network could be built, which was one of our goals.

The experiments performed did demonstrate to us that all optical neural networks were possible, but they also pointed out a serious deficiency of the bias subtraction approach. This approach is only appropriate when the number of negative connections a node makes with other nodes is a constant. It is not necessary that the connection pattern be space invariant but the constant fan-out of the node, at least for inhibitory connections, is important, otherwise the threshold point will be a node dependent. A network with this behavior is not uniform or flexible enough to be useful.

The following conclusion was reached: Since all optical nonlinearities function on the optical intensity, and since the only way of representing negative quantities with optical intensity is through the bias subtraction technique, optical nonlinearities are inappropriate for the implementation of neural networks. The obvious corollary is that an electronic implementation of the node function is the only general approach. We, therefore, envision a node plane such as shown in Fig. 15. General bipolar interconnections can be obtained by dedicating two integrating detectors for each node; one detector is used for negative connections and the other for positive connections. The integrated output of each detector is transferred to a storage node. The difference of these two values is implemented electronically. A nonlinear mapping is applied and the electrical output signal drives a light source. The approach is basically the same as that used by Psaltis and Farhat[28] in their original work except that a 2-D array of inte-

ACCOMPLISHMENTS (cont.)

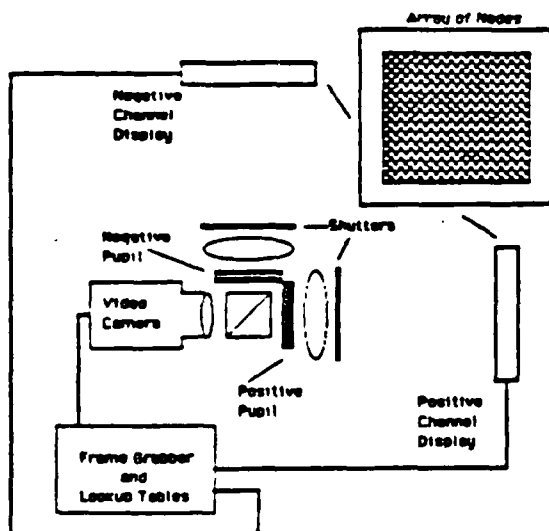
FIG 13 a

OPTICAL IMPLEMENTATION:

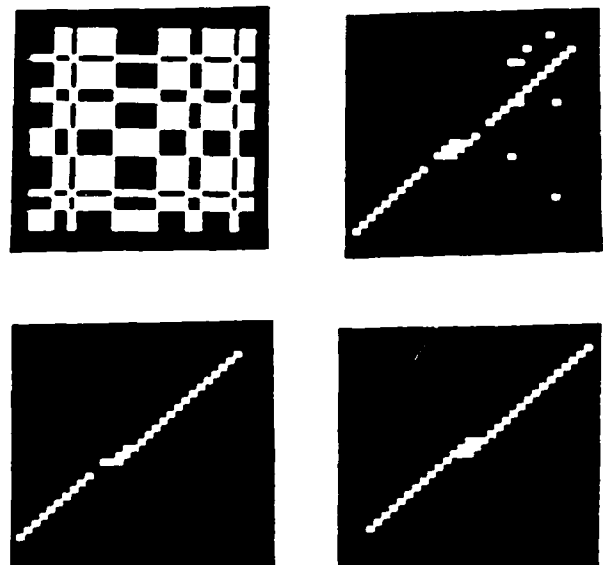
CONSTRUCTION AND DEMONSTRATION OF OPTICAL SYSTEM FOR RADON SPACE FEATURE EXTRACTION AS PRECURSOR TO OPTICAL NEURAL NET.

IDENTIFICATION AND EVALUATION OF APPROACHES TO IMPLEMENTATION OF OPTICAL NEURAL NETS.

DEMONSTRATION OF OPTICAL NEURAL NETWORK FOR IMPLEMENTATION OF MARR-POGGIO STEREOPSIS NETWORK AS EXAMPLE OF SYSTEM WITH SPACE INVARIANT CONNECTION PATTERN.



Two-channel optical system for implementing the stereo algorithm



Example of convergence behavior of the stereo network obtained with optical neurocomputer. The first image again shows the starting point of the network. The next three images show the next three iterations of the network. The results are essentially identical to those obtained in Fig. 3. above using a standard digital computer.

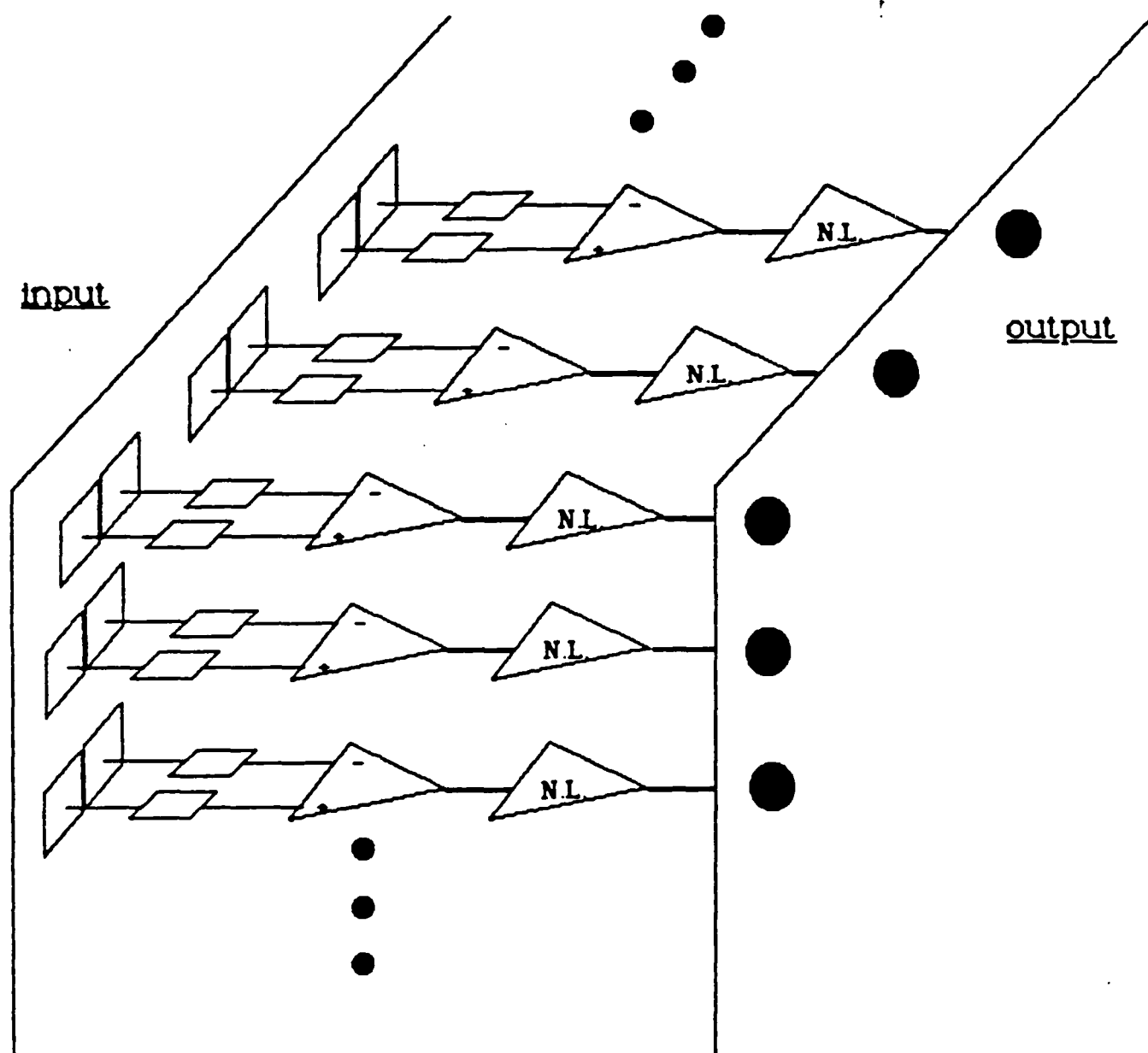


Fig. 15:

Two dimensional electronic node plane.

Two detectors for each node transfer integrated charge to a storage node. A difference amplifier subtracts these signals and a nonlinear amplifier drives an optical source.

grated electronic nodes is considered here. The individual nodes in the system can be addressed by the controller or the subproblem memory of Fig. 13 either electronically or optically.

The requirements on the node output (light source) are that it be bright enough to allow for a reasonably short integration time on the detectors and that it have a very high contrast ratio so that the off signal is truly off. If this is not so, the accumulation of many "off" signals at a node input can exceed the threshold and cause the node value to change incorrectly. The other consideration for the optical output is whether it should be temporally coherent or not. This depends on the particular method chosen for implementing the connections.

From our standpoint, there are few general comments concerning the requirements for a general connection element. First, it must be general (i.e. be capable of implementing any space variant connection pattern). Second, it must be clean. By this we mean the following: the creation of a particular connection between two nodes can not create an undesired connection between two other nodes. And third, the connection pattern must be able to be rapidly changed to a new connection pattern to solve a new subproblem.

We began to explore two technologies for implementing connection patterns: spatially multiplexed planar holograms and lenslet-array/mask systems. Spatially multiplexed holograms, such as those described by Jenkins[38,39], are capable of general interconnectivity. The key question is how many nodes can be interconnected with sufficient accuracy. Jenkins has analyzed the problem from the standpoint of the connectivity of digital optical gates and has estimated that an array of 100x100 gates can be interconnected using a single 10cm x 10cm e-beam fabricated hologram. The situation is different for neural networks because the connection weights are continuous valued and the fan-in to the nodes is typically very large. On the other hand, neural architectures are often much more tolerant of errors in the system.

The investigation of e-beam holograms for general neural network interconnections will proceed along three lines. First, an analysis of the interconnection capacity of holographic elements will be performed using an associative memory model. A statistical approach similar to that described in our paper on non-zero diagonal connection matrices[16] will be used. The errors in connection strength caused by finite apertures and discrete number representations will be modeled, and their effect on the performance of the network determined. Another approach will be to write a computer program that models the holographic interconnection element and, using it, study the behavior of a network when implemented with this technology. Physical effects such as scatter and alignment can be studied in this manner. Finally, e-beam holograms will be fabricated and investigated for their performance. A set up such as that shown in Fig. 16 will allow us to evaluate these holographic interconnect elements. In the system of Fig. 16, the node outputs (sources) can be controlled via the computer and frame buffer, and converted to a coherent optical signal by the spatial light modulator (Hughes Liquid Crystal Light Valve). The optical signal at the output (node

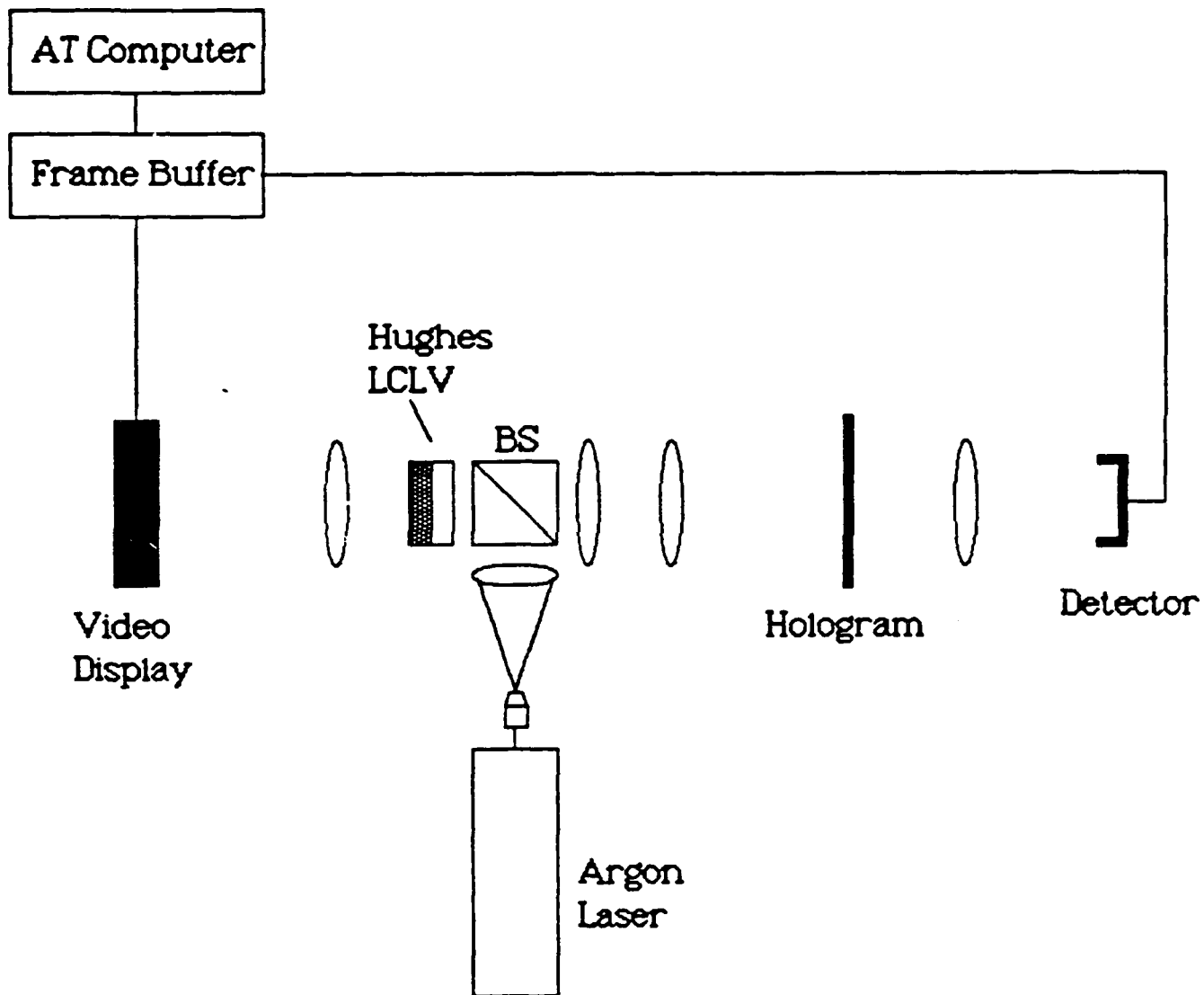


Fig. 16:
Optical setup for testing the performance
of a holographic connection element.

input plane) can be sensed by any of a host of imaging or nonimaging detectors to study the properties of the light signal and therefore the properties of the holographic interconnect element.

The holographic interconnect technology is amenable to being modified or updated at a reasonably high rate. A system that stored multiple holographic interconnections on a large disk structure, whose regions could be rapidly accessed, is a possibility. Also a possibility is a juke box approach, where connection patterns are stored, accessed, and inserted into the neural net computing engine by a high speed mechanical device.

The other technology for interconnection we intend to investigate is that of lenslet arrays. Glaser[37] has discussed how these arrays can be used, in conjunction with a mask, to implement a general connection pattern. His focus was on the implementation of general linear transformations, but much of his discussion is germane to neural networks as well. The issues of aberrations, mask alignment, and illumination are certainly key ones that need to be carefully analyzed if this technology is going to work at a scale that is useful for optical neural networks. The main advantage of this approach is that the light sources can be incoherent.

We have recently purchased a 40x40 element lenslet array. We intend to investigate this device in the context of a winner-take-all network. The mask structure for this network is relatively simple and can be fabricated either with the e-beam facility or with the microdensitometer film-writing instrument at the Optical Sciences Center. The actual construction of the network will use a video display device as the node output and a video camera as the node input. Non-linear node responses will be performed by the computer and frame buffer. The demonstration of this network will undoubtedly delineate the problems associated with lenslet array/mask interconnects.

On a conceptual level the lenslet array approach to interconnection is also capable of being rapidly modified in the same way that the holographic systems are modifiable; instead of repositioning a hologram, a new mask is repositioned. However, the repositioning of the mask is far more sensitive to position errors than the hologram. The mask position tolerance is extremely small for lateral position, angular position, and focus. The updating of a series of masks does seem to pose a serious problem. One solution would be to position a lenslet array with each mask and insert the whole structure into the optical system. This would increase the positional tolerance tremendously.

5 Summary of Personnel and Publications

Below is a list of professional personnel associated with this grant:

- A.F. Gmitro, Assistant Prof. Diagnostic Radiology, Yale U.
- G.R. Gindi, Assistant Prof. Diagnostic Radiology and Electrical Engineering, Yale U.
- James Ong, Graduate Student, Department Computer Science, Yale U.
- Donald Delorie, Programmer, Division of Imaging Science, Yale U.
- Kannan Parthasarathy, Graduate Student, Department of Electrical Engineering, Yale U.
- Tony Zador, Graduate Student, Section of Neuroanatomy, Yale U.

Below is a list of publications resulting from this grant:

- G. R. Gindi and D.H. Delorie, "Indexing shapes for Recognition", 5th Intl. Conf on Robot Vision and Sensory Controls, Proc. SPIE, **729**, 28-35, Cambridge, Mass (1986)
- G.R. Gindi and D.H. Delorie, "Shape Representation in a Mainpart/Subpart Hierarchy", Proc. Topical Meeting on Machine Vision, Op. Soc. Am., Lake Tahoe, Nev., pp.117-120 (1987)
- G.R. Gindi, A.F. Gmitro, and K. Parthasarathy, "Winner-Take- All Networks and Associative Memory", Proc. First IEEE Annual Conference on Neural Networks, pp. 607-614 San Diego August (1987)
- A. F. Gmitro, and G. R. Gindi, "Optical Neurocomputer for Implementation of the Marr-Poggio Stereo Algorithm", IEEE Conference on Neural Networks, pp.599-606, San Diego, CA, June (1987).
- G.R. Gindi, A.F. Gmitro, and K. Parasarathy, "Hopfield Model Associative Memory with Nonzero Diagonal Terms in Memory Matrix", Applied Optics, **37**, 129-135 (1988).
- G. R. Gindi and A. F. Gmitro, "Optical Feature Extraction via the Radon Transform," Opt. Eng. **23**, 499 (1984).

Below is a list of abstracts and technical reports associated with this grant:

- J. Ong and G.R. Gindi, "Description and Indexing of 2-D Curved Visual Objects", TR 8608, Division of Imaging Science, Yale U., (1986)
- G.R. Gindi and A.F. Gmitro, "Multilayer Neural Net and Its Optical Implementation", J. Opt. Soc. Am. A, **3**, 32 (1986)
- G.R. Gindi and A.F. Gmitro, "Associative Memory with Self-Connected Nodes", J. Opt. Soc. Am. A, **4**, 117 (1987)

- G.R. Gindi, "SQUARESWORLD-Initial Results of a Connectionist Implementation for Object Recognition", TR 8602, Yale U. Division of Imaging Science (1986)
- D.H. Delorie and G.R. Gindi, "SQUARESVILLE: An Interactive Neural-Net Simulator", TR-8611, Yale U. Div. of Imaging Science (1986)
- E. Mjolsness, G. Gindi, P. Anandan, and T. Zador, "Objective Functions in Recognition", AAAI Spring Symposium on Physical and Biological Approaches to Computational Vision, (Stanford 1988) accepted for presentation.
- E. Mjolsness, G. Gindi, T. Zador, P. Anandan, "Objective Functions for Recognition: A Neural Network That Incorporates Inheritance and Abstraction", submitted to 1988 Snowbird Conference on Neural Networks for Computing.

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